Prediction of Energy Expenditure and Physical Activity in Preschoolers

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ABSTRACT

BUTTE, N. F., W. W. WONG, J. S. LEE, A. L. ADOLPH, M. R. PUYAU, and I. F. ZAKERI. Prediction of Energy Expenditure and Physical Activity in Preschoolers. *Med. Sci. Sports Exerc.*, Vol. 46, No. 6, pp. 1216–1226, 2014. **Purpose**: Accurate, nonintrusive, and feasible methods are needed to predict energy expenditure (EE) and physical activity (PA) levels in preschoolers. Herein, we validated cross-sectional time series (CSTS) and multivariate adaptive regression splines (MARS) models based on accelerometry and heart rate (HR) for the prediction of EE using room calorimetry and doubly labeled water (DLW) and established accelerometry cut points for PA levels. **Methods**: Fifty preschoolers, mean ± SD age of 4.5 ± 0.8 yr, participated in room calorimetry for minute-by-minute measurements of EE, accelerometer counts (AC) (Actiheart and ActiGraph GT3X+), and HR (Actiheart). Free-living 105 children, ages 4.6 ± 0.9 yr, completed the 7-d DLW procedure while wearing the devices. AC cut points for PA levels were established using smoothing splines and receiver operating characteristic curves. **Results**: On the basis of calorimetry, mean percent errors for EE were −2.9% ± 10.8% and −1.1% ± 7.4% for CSTS models and −1.9% ± 9.6% and 1.3% ± 8.1% for MARS models using the Actiheart and ActiGraph+HR devices, respectively. On the basis of DLW, mean percent errors were −0.5% ± 9.7% and 4.1% ± 8.5% for CSTS models and 3.2% ± 10.1% and 7.5% ± 10.0% for MARS models using the Actiheart and ActiGraph+HR devices, respectively. Applying activity EE thresholds, final accelerometer cut points were determined: 41, 449, and 1297 cpm for Actiheart *x*-axis; 820, 3908, and 6112 cpm for ActiGraph vector magnitude; and 240, 2120, and 4450 cpm for ActiGraph *x*-axis for sedentary/light, light/moderate, and moderate/vigorous PA (MVPA), respectively. On the basis of confusion matrices, correctly classified rates were 81%–83% for sedentary PA, 58%–64% for light PA, and 62%–73% for MVPA. **Conclusions**: The lack of bias and acceptable limits of agreement affirms the validity of the CSTS and MARS models for the prediction of EE in preschool-aged children. Accelerometer cut points are satisfactory for the classification of sedentary, light, and moderate/vigorous levels of PA in preschoolers. **Key Words:** ACCELEROMETER, HEART RATE, ACTIHEART, ACTIGRAPH, CALORIMETRY

Accurate, nonintrusive, and feasible techniques to predict energy expenditure (EE) and physical activity (PA) levels under free-living conditions facilitate the study of energy regulation and habitual PA of preschool-age children. Accelerometers and miniaturized heart rate (HR) monitors permit the measurement of elements of these complex physiologic processes, which can be used in advanced mathematical models to predict EE and PA levels. Because the relationships between HR, accelerometer output, and EE differ in preschoolers compared with older children, prediction equations require development and validation in this age group (21,28,30,34).

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We recently developed cross-sectional time series (CSTS) and multivariate adaptive regression splines (MARS) models for the prediction of EE based on minute-by-minute measurements of room respiration calorimetry, accelerometry, and HR monitoring in 69 preschoolers (41). In this previous study, commercially available accelerometers/HR monitors (Actiheart and ActiGraph GT3X+) were used. The advantage of room respiration calorimetry for the development of EE prediction equations is the high density of continuous (not just steady state) EE data for several hours obtainable on children undergoing structured as well as unstructured activities, unencumbered by respiratory gas collection equipment.

Relative to the EE measured by calorimetry, the mean percent errors of the CSTS and MARS models indicated a lack of bias and acceptable limits of agreement at the group and individual levels (41). The mean ± SD percent errors predicting awake EE (−1.1% ± 8.7%, 0.3% ± 6.9%, and −0.2% ± 6.9%) with CSTS models were slightly higher than those with MARS models (−0.7% ± 6.0%, 0.3% ± 4.8%, and −0.6% ± 4.6%) for Actiheart, ActiGraph, and ActiGraph+HR devices, respectively. Predicted awake EE values were within ±10% for 81%–87% of individuals for CSTS models and for 91%–98% of individuals for MARS models. Concordance correlation coefficients (CCC) were excellent: 0.936, 0.931, and 0.943 for CSTS EE models and 0.946, 0.948, and 0.940 for MARS EE models for Actiheart, ActiGraph, and ActiGraph+HR devices, respectively. The satisfactory performance of the CSTS and MARS models for the prediction of EE in preschoolers warranted independent validation.

In addition, accelerometers can be used to assess PA levels in preschool-age children (20,35). Accelerometer cut points for sedentary, light, moderate, and vigorous PA levels in preschoolers have been identified primarily using direct observation (5,8,9,24,28,31,36), although a few studies have used respiration calorimetry (2,21,22) as the criterion method. While essential for identifying the types of activities, direct observation is imprecise for the quantification of the intensity of PA and thus the level of EE. If the rationale for assessing PA is to capture a component of the child's energy balance, validation of accelerometers is preferably based on calorimetric measurements representing the range of PA characteristic of preschoolers (18,38).

In this study, we validated CSTS and MARS models for the prediction of minute-by-minute EE and established accelerometer cut points for PA levels in preschool-age children. Our specific aims were 1) to validate CSTS and MARS models based on observable child characteristics, HR, and accelerometer counts (AC) for the prediction of minute-by-minute EE against room respiration calorimetry; 2) to validate the CSTS and MARS models against 7-d mean total energy expenditure (TEE) using the doubly labeled water (DLW) method under free-living conditions; and 3) to define AC cut points for sedentary, light, moderate, and vigorous levels of PA in preschool-age children.

MATERIALS AND METHODS

Study design. The overall study design called for two independent cohorts to develop and validate prediction equations for EE in preschool-age children. The children were recruited stratified by age and sex, using fliers at local clinics and preschool centers in Houston. For model development, CSTS and MARS models were developed based on minute-by-minute measurements of room respiration calorimetry, accelerometry, and HR monitoring in 69 preschoolers and published elsewhere (41). For model validation, the CSTS and MARS models were validated also based on minute-by-minute measurements of room respiration calorimetry, accelerometry, and HR monitoring in an independent set of 50 preschoolers. The two sets were not significantly different with respect to age, sex, weight, height, or body mass index (BMI) *z*-score. The validation protocol using calorimetry entailed a 7-h visit to the Children's Nutrition Research Center metabolic research unit. In addition, both the development (n = 69) and validation (n = 50) cohorts were asked to complete the 7-d DLW protocol for model validation. A total of 105 of these children successfully completed the 7-d DLW validation protocol under free-living conditions. The DLW measurements were considered independent because these data were not used in the development of the models. The 7-d protocol entailed the DLW method, concomitant with accelerometry and HR monitoring.

The Institutional Review Board for Human Subject Research for Baylor College of Medicine and Affiliated Hospitals approved the protocol. All parents/primary caretakers gave written informed consent to participate in this study.

Subjects. Healthy preschool-age children, ages 3 to 5 yr old, were eligible for this study. Children on prescription drugs or with chronic diseases, including endocrine disorders, asthma treated with steroids, sleep apnea, and any condition that interfered with PA, were excluded from the study.

Anthropometry. Body weight to the nearest 0.1 kg was measured with a digital balance, and height to the nearest 1 mm was measured with a stadiometer. BMI was calculated as weight/height^2 (kg·m^{-2}). Nonoverweight was defined as <85th percentile for BMI, and overweight/obese was defined as ≥85th percentile for BMI, according to the US Centers for Disease Control and Prevention (15).

Accelerometry and HR monitoring: Actiheart. Actiheart (CamNtech Ltd, Cambridge, UK) is a small (thickness = 7 mm, diameter = 33 mm, total weight = 10 g) device equipped with a uniaxial accelerometer and electrocardiogram signal processor. Actiheart was attached to the chest using two electrodes (Skintact Premier; Leonhard Lang GmbH, Innsbruck, Austria). The main sensor was attached left of the sternum and secured with the adhesive tab on the electrode. The lead was attached parallel along the midclavicular line at the level of the third intercostal space (upper position) or just below the left side of the chest (lower position). The electrodes were checked and replaced if there was poor adhesion. At the conclusion of the calorimetry protocol or 7-d DLW protocol, the data were downloaded into Excel. HR and AC data acquisition by Actiheart was set at 15-s epochs. Actiheart data were collapsed into 60-s epochs and aligned with the minute-by-minute EE data. HR data were filtered with an upper cut point of 220. The lower cut point for HR filtering was set at a value of 10% below the 20-min minimal HR observed for each subject during sleep.

Accelerometry: ActiGraph GT3X+. ActiGraph GT3X+ (ActiGraph, Pensacola, FL), a triaxial accelerometer, was used to measure the amount and frequency of movement of the children. The monitor is compact and lightweight, measuring 4.6 cm × 3.3 cm × 1.5 cm with a weight of 19 g. The output includes activity counts (vertical x, horizontal y, and diagonal z axes), vector magnitude, which is equal to the square root of ((amplitude x)^2 + (amplitude y)^2 + (amplitude z)^2), and number of steps taken. The inclinometer feature of ActiGraph GT3X+ indicates subject position (1 = standing, 2 = lying down, 3 = sitting) and identifies periods when the device has been removed (0 = monitor off). Each sample was summed over a

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60-s epoch. The ActiGraph monitors were affixed above the iliac crest of the right side of the hip with an adjustable elastic belt. Data acquisition storage was set at 15-s epochs. Data were downloaded into Excel and collapsed into 60-s intervals to align with calorimeter minute-by-minute data.

Room respiration calorimetry. While inside a room respiration calorimeter, the child was instructed to follow a protocol of PA designed to characterize minute-by-minute EE, AC, and HR relationships characteristic of this age group. Oxygen consumption ($\dot{V}O_2$) and carbon dioxide production ($\dot{V}CO_2$) were measured continuously in a 19-m^3 fast-response room calorimeter, the performance of which has been described previously (19). EE was computed using the Weir equation (37). $\dot{V}O_2$, $\dot{V}CO_2$, EE, and HR were averaged at 1-min epochs. The calorimeters were decorated as a playroom for preschool-age children. While in the calorimeter, all children were asked to perform a series of PA in the same order between 0900 and 1600 h under staff supervision. Activities included watching television, coloring, playing video games, playing with child's kitchen and other toys, dancing, performing aerobics, running in place, and napping. In between the series of scheduled PA, the children were given "free time" to engage in light activities of their choice while in the calorimeter. The staff recorded minute-to-minute observations of the child's activities. The children were given lunch at 1130 h outside the calorimeter and snacks around 0930 and 1430 h inside the calorimeter. The calorimeter protocol is described fully in our previous publication (41).

DLW method. TEE was measured over a 7-d period using the DLW method (1). After collection of the baseline urine samples, each participant received by mouth 0.086 $g \cdot kg^{-1}$ body weight of ^2H_2O at 99.9 atom% ^2H and 1.38 $g \cdot kg^{-1}$ body weight of $H_2{}^{18}O$ at 10 atom% ^{18}O (Isotec, Miamisburg, OH). The bottle holding the $^2H_2{}^{18}O$ was rinsed three times with approximately 5–10 mL of drinking water, and the children were asked to finish drinking all the rinses. Parents were given instructions on the proper procedure to collect a daily urine sample at home, record the date and time of the sample collection, and transfer 1 mL of urine sample each into two o-ring cryovials. Seven postdose urine samples were collected at home on days 1–7. The urine samples were stored frozen before transfer for analysis in the Gas Isotope Ratio Mass Spectrometry Laboratory at the Children's Nutrition Research Center.

Urine samples were analyzed for stable hydrogen and oxygen isotopic enrichment by gas isotope ratio mass spectrometry (40). For stable hydrogen isotope ratio measurements, 10 μL of urine without further treatment was reduced to hydrogen gas with 200 mg of zinc reagent at 500°C for 30 min (39). The $^2H/^1H$ isotope ratios of the hydrogen gas were measured with a Finnigan Delta-E gas isotope ratio mass spectrometer (Finnigan MAT, San Jose, CA). For stable oxygen isotope ratio measurements, 100 μL of urine was allowed to equilibrate with 300 mbar of CO_2 of known ^{18}O content at 25°C for 10 h using a VG ISOPREP-18 water–CO_2 equilibration system (VG Isogas, Ltd., Cheshire, UK). At the end of the equilibration, the $^{18}O/^{16}O$ isotope ratios of the CO_2 were measured with a VG SIRA-12 gas isotope ratio mass spectrometer (VG Isogas, Ltd.).

The isotopic results were normalized against two international water standards: Vienna-Standard Mean Ocean Water and Standard Light Antarctic Precipitation (11). The isotope dilution spaces for ^2H (N_H) and ^{18}O (N_O) were calculated as follows:

$$N_H \text{ or } N_O\,(\text{mol}) = \frac{d\,A\,E_\alpha}{18.02\alpha\,E_d} \qquad [1]$$

where d is the dose of ^2H_2O or $H_2{}^{18}O$ in grams, A is the amount of laboratory water in grams used in the dose dilution, α is the amount of ^2H_2O or $H_2{}^{18}O$ in grams added to the laboratory water in the dose dilution, E_α is the rise in ^2H or ^{18}O abundance in the laboratory water after the addition of the isotopic water, and E_d is the rise in ^2H or ^{18}O abundance in the urine samples at time 0 obtained from the zero-time intercepts of the ^2H and ^{18}O decay curves in the urine samples. $\dot{V}CO_2$ was calculated from the fractional turnover rates of ^2H (k_H) and ^{18}O (k_O) as follows:

$$\dot{V}CO_2\,(\text{mol}\cdot\text{d}^{-1}) = 0.45537\,(k_O N_O - k_H N_H) \qquad [2]$$

$\dot{V}CO_2$ was converted to TEE using the Weir equation (37) as follows:

$$\text{TEE}\,(\text{kcal}\cdot\text{d}^{-1}) = 22.4\,(1.106\dot{V}CO_2 + 3.941\dot{V}O_2) \qquad [3]$$

where $\dot{V}O_2$ was calculated using the relationship $\dot{V}O_2 = \dot{V}CO_2/\text{FQ}$, assuming a food quotient (FQ) (3) equal to 0.86. Activity energy expenditure (AEE) was calculated as the difference between TEE and basal metabolic rate (BMR) computed according to Schofield et al. (27) and thermic effect of food (TEF), which was assumed to be equal to 10% of TEE, as follows:

$$\text{AEE}\,(\text{kcal}\cdot\text{d}^{-1}) = \text{TEE} - \text{BMR} - 0.1\text{TEE}. \qquad [4]$$

CSTS and MARS models. CSTS is a parametric method based on regression and time series analysis to model a collection of correlated data (6,13). In the CSTS model, minute-by-minute EE is predicted based on HR, AC, and other subject covariates. A CSTS or mixed regression model with random intercepts and random slopes was used. The model contains population-specific parameters describing average trends, which are independent vectors of random effects associated with covariates, and subject-specific parameters describing how the response of the individuals deviates from the mean response over time. A distinguishing feature of the CSTS model is that the regression coefficients may differ across individuals, such that each individual has his or her own regression parameters.

In the final CSTS model, there are three categories of predictor variables (41). The first category is the time-varying variables, namely HR, HR^2, and 1- and 2-min lead and lag values of HR; and AC, AC^2, and 1- and 2-min lead and lag values of AC (x, y, and z axes); and steps and 1- and 2-min lead and lag values of steps; and position. The second category is child-specific characteristics—sex, age, height, weight, and sleep HR. The third category is interaction terms between HR, AC, and other variables.

MARS is a nonparametric regression method that approximates a complex nonlinear relationship by a series of spline functions on different intervals of the independent variable (10). A key property of MARS over global parametric models is its ability to operate locally. MARS allows inclusion of interaction terms that are active in a localized region of the variables involved. Splines are generally defined to be piecewise polynomial functions. The breakpoints marking the transition from one polynomial to the next are referred to as knots (or joint points).

In the MARS model, the regression function $f(x)$ is written as an additive function of the product basis functions:

$$\hat{f}_M(x) = \beta_0 + \sum_{m=1}^{M} \beta_m B_m(x) \quad [5]$$

where β_0 is the coefficient of the constant basis function $B_0(x) = 1$, $B_m(x)$ is the m^{th} basis function that may be a single spline function or product of two or more, β_m is the coefficient of the basis function, and M is the number of basis functions in the model. The MARS algorithm starts with the constant basis function $B_0(x)$ in the model. The final MARS entailed linear combinations of 30–50 basis functions that used subject characteristics (age, sex, weight, height, and sleeping HR), HR, HR^2 and AC, AC^2, and 1- and 2-min lag and lead values of HR and AC; steps and 1- and 2-min lag and lead values of steps; and appropriate interaction terms (41).

Implementation of the CSTS and MARS models. Application of the CSTS and MARS models to the AC and HR data obtained during calorimetry entailed downloading the data and collapsing the data into 60-s epochs to align with the calorimeter minute-by-minute data. Implementation of the CSTS and MARS models over the 7-d DLW period required several decision points. A 60-s epoch was used for the Actiheart and ActiGraph GT3X+ data. Nonwear time was defined as 20 min or more of consecutive zero counts, if the interval was not identified as nighttime sleep, nap time, or device removal for bathing or aquatic activities in the records completed by the parents. Visual inspection of the AC and HR data was also used to assess nonwear time as well as sleep and awake times. A valid day required a minimum of 1000 $\text{min}\cdot\text{d}^{-1}$ of wear time. The sufficient number of days of wearing time was defined as a minimum of four valid days including at least one weekend day (33).

STATA (release 11; StataCorp LP, College Station, TX) was used to implement the CSTS and MARS models. EE was predicted minute-by-minute from child characteristics, AC, HR, steps, and position. In the DLW protocol, the minute-by-minute EE values were summed over the 24-h period to compute TEE. If the 24-h period had incomplete data due to nonwear time or technical problems with device, the average minute EE was used to extrapolate to 1440 min. The average TEE over the 7 d was computed for comparison with TEE measured by DLW.

Statistics. Data are summarized as means ± SD. Descriptive statistics were performed using STATA (release 11; StataCorp LP). Goodness-of-fit methods were used to assess and compare competing models based on their agreement between the measured values and model estimates derived from CSTS or MARS. Mean absolute errors, mean percent errors, and root mean square errors (RMSE) were computed to assess the accuracy of the CSTS and MARS models against room respiration calorimetry and DLW. Concordance between the observed and predicted EE was assessed using the Bland and Altman graphical method (4). While the Bland–Altman (4) diagnostic plot of the difference versus the mean can provide insight into the measurement differences between two methods, it does not provide a single measure of agreement. In addition, the concordance correlation coefficient (CCC) that is considered appropriate for measuring agreement when the data are measured on a continuous scale was applied (16,17).

To define AEE ($\text{kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$) levels for sedentary, light, moderate, and vigorous PA, smoothing splines curve fitting with 10 knots was applied to established HR cut points (110, 140, and 160 bpm) for PA levels in preschoolers based on direct observation (7,23). The smoothing parameter was automatically selected using generalized cross-validation (12). Next, smoothing splines curve fitting was applied to AEE and AC to identify accelerometer cut points for Actiheart and ActiGraph. In addition, receiver operating characteristic (ROC) curves were constructed, and sensitivity and specificity were computed to identify cut points. The ROC curve was created by computing sensitivity and 1 − specificity at different candidate thresholds and then plotting these points (12). The cut point that maximized the classification rates (sensitivity + specificity) was selected. It is important to note that the cut points determined by this technique may still not be the best for the classification, and since the thresholds from smoothing splines were a starting point on ROC curves, the majority vote (combining information from smoothing splines and ROC curves) was used to determine the optimal thresholds (14). Lastly, to determine the best classification thresholds, a confusion matrix was constructed. The accuracy of the classifier from the confusion matrix was calculated as the ratio of the sum of the main diagonal elements divided by the total sum of the entries. Hence, the proportion of the correctly classified cases indicates the accuracy of the candidate classifier.

RESULTS

Calorimeter validation of the CSTS and MARS models. Fifty preschool-age children, mean age 4.5 ± 0.8 yr, were enrolled into the calorimeter validation cohort. The cohort consisted of 10 white, 16 black, 18 Hispanic, and 6 multiracial children and was balanced for age and sex.

TABLE 1. Observed data of the calorimeter validation cohort.

Age (yr)	4.5 ± 0.8 (3.1 to 5.9)[a]
Weight (kg)	17.6 ± 2.6 (13.7 to 24.2)
Height (m)	1.06 ± 0.07 (0.91 to 1.21)
BMI *z*-score	−0.05 ± 0.86 (−2.07 to 1.86)
Calorimeter monitoring time (min)	218 ± 53 (76 to 302)
Energy expenditure (kcal·min^{-1})	1.06 ± 0.21 (0.32 to 5.08)
Heart rate (bpm)	113 ± 10 (59 to 217)
Actiheart *x*-axis counts (cpm)	162 ± 108 (0 to 4150)
ActiGraph *x*-axis counts (cpm)	651 ± 291 (0 to 10,698)
ActiGraph *y*-axis counts (cpm)	713 ± 266 (0 to 8032)
ActiGraph *z*-axis counts (cpm)	760 ± 300 (0 to 7966)
Vector magnitude (cpm)	1303 ± 493 (0 to 13,077)
Steps (steps per minute)	11 ± 5 (0 to 199)

[a]Data are given as means, standard deviation, and ranges; n = 25 boys and 25 girls.
BMI = body mass index; cpm = counts per minute.

Twelve percent of the children were overweight or obese. Mean rates of EE, HR, AC, and steps observed during the entire calorimetry monitoring are presented in Table 1. A wide range of EE, HR, AC, and steps was captured during calorimetry, representing minimal rates during sleep to near-maximum rates while running in place.

CSTS and MARS models were evaluated for all minute-by-minute calorimeter data, as well as separately for awake and sleep periods. Mean absolute errors, mean percent errors, and RMSE for all EE, awake EE, and sleep EE are presented in Table 2. The mean percent errors for all EE (1.06 ± 0.07 kcal·min^{-1}) were −2.9% ± 10.8% and −1.1% ± 7.4% for CSTS models and −1.9% ± 9.6% and 1.3% ± 8.1% for MARS models using the Actiheart and ActiGraph+HR devices, respectively. The corresponding RMSE values were 0.117 and 0.075 for the CSTS models and 0.107 and 0.085 kcal·min^{-1} for the MARS models using the Actiheart and ActiGraph+HR devices, respectively. Errors were not statistically associated with age, sex, weight, height, or BMI *z*-score.

The mean absolute errors and RMSE for awake EE (1.11 ± 0.18 kcal·min^{-1}) were similar to those for all EE. Sleep EE (0.58 ± 0.08 kcal·min^{-1}) was evaluated in 21 preschoolers who napped during the visit. The mean absolute errors and RMSE were lower and the mean percent errors were greater during the sleep than during the awake periods because of the lower rates of EE during sleep. On the basis of the ActiGraph device without HR, the mean absolute errors, percent errors, and RMSE for the ActiGraph models were slightly lower than those for the ActiGraph+HR models.

Bland–Altman plots of the differences between EE measured in the calorimeter and predicted by the CSTS and MARS models for all EE are presented for the validation cohort in Figure 1A. Mean percent errors for all data were not significantly different from zero. By linear regression, there was no significant relationship between the method difference and the size of the measurements. The 95% limits of agreement (± 0.20 kcal·min^{-1}) demonstrated close agreement between the measured values and the model predictions. The ActiGraph+HR CSTS model had the narrowest 95% limits of agreement, consistent with the lowest RMSE. The CCC were 0.91 and 0.93 between the measured and predicted minute-by-minute values for the CSTS models and 0.88 and 0.86 for the MARS models, using Actiheart and ActiGraph+HR, respectively.

DLW validation of the CSTS and MARS models. In the 105 children, ages 4.6 ± 0.9 yr, who completed the DLW procedure while simultaneously wearing Actiheart and ActiGraph, the monitors were worn for an average of 6.7 ± 0.7 d; 94% of the children had six or seven valid days. Mean weight and height were 18.3 ± 3.7 kg and 107 ± 7.6 cm, respectively. Mean TEE over the 7-d period was 1205 ± 184 kcal·d^{-1}.

CSTS and MARS models were applied to the minute-by-minute HR and AC data to predict TEE for each 24-h period and averaged over the 7-d period. Mean absolute errors, mean percent errors, and RMSE for the predicted TEE by the CSTS and MARS models using Actiheart and ActiGraph+HR devices are presented in Table 3. The mean percent errors were −0.5% ± 9.7% and 4.1% ± 8.5% for CSTS models and 3.2% ± 10.1% and 7.5% ± 10.0% for MARS models using the Actiheart and ActiGraph+HR devices, respectively. Bland–Altman plots illustrated a nonsignificant mean bias for the Actiheart CSTS model and a positive mean bias for the other models (P < 0.02). The method difference was not independent of the size of the TEE measurement (P < 0.01). The 95% limits of agreement

TABLE 2. Prediction errors of the CSTS and MARS models for the prediction of EE versus room respiration calorimetry.

	CSTS Model			MARS Model		
	Actiheart	ActiGraph	ActiGraph + HR	Actiheart	ActiGraph	ActiGraph + HR
Mean absolute error (kcal·min^{-1})						
All data	−0.034 ± 0.114[a]		−0.014 ± 0.075	−0.027 ± 0.104		0.006 ± 0.085
Awake	−0.039 ± 0.121	−0.005 ± 0.07	−0.012 ± 0.082	−0.033 ± 0.109	0.009 ± 0.071	0.003 ± 0.088
Sleep	0.015 ± 0.088		−0.013 ± 0.061	0.046 ± 0.07		0.053 ± 0.055
Mean percent error (%)						
All data	−2.9 ± 10.8		−1.1 ± 7.4	−1.9 ± 9.6		1.3 ± 8.1
Awake	−3.1 ± 10.9	−0.2 ± 6.7	−0.6 ± 7.5	−2.5 ± 9.6	1.1 ± 6.6	0.8 ± 7.9
Sleep	2.5 ± 16		−2.7 ± 11.9	8.6 ± 12.6		10.1 ± 9.8
RMSE (kcal·min^{-1})						
All data	0.117		0.075	0.107		0.085
Awake	0.126	0.070	0.082	0.112	0.070	0.087
Sleep	0.089		0.059	0.080		0.073
r^2	0.873	0.876	0.898			

[a]n = 50 (n = 21 for sleep); data are given as means and standard deviation.
CSTS = cross-sectional time series; EE = energy expenditure; HR = heart rate; MARS = multivariate adaptive regression splines; RMSE = root mean square error.

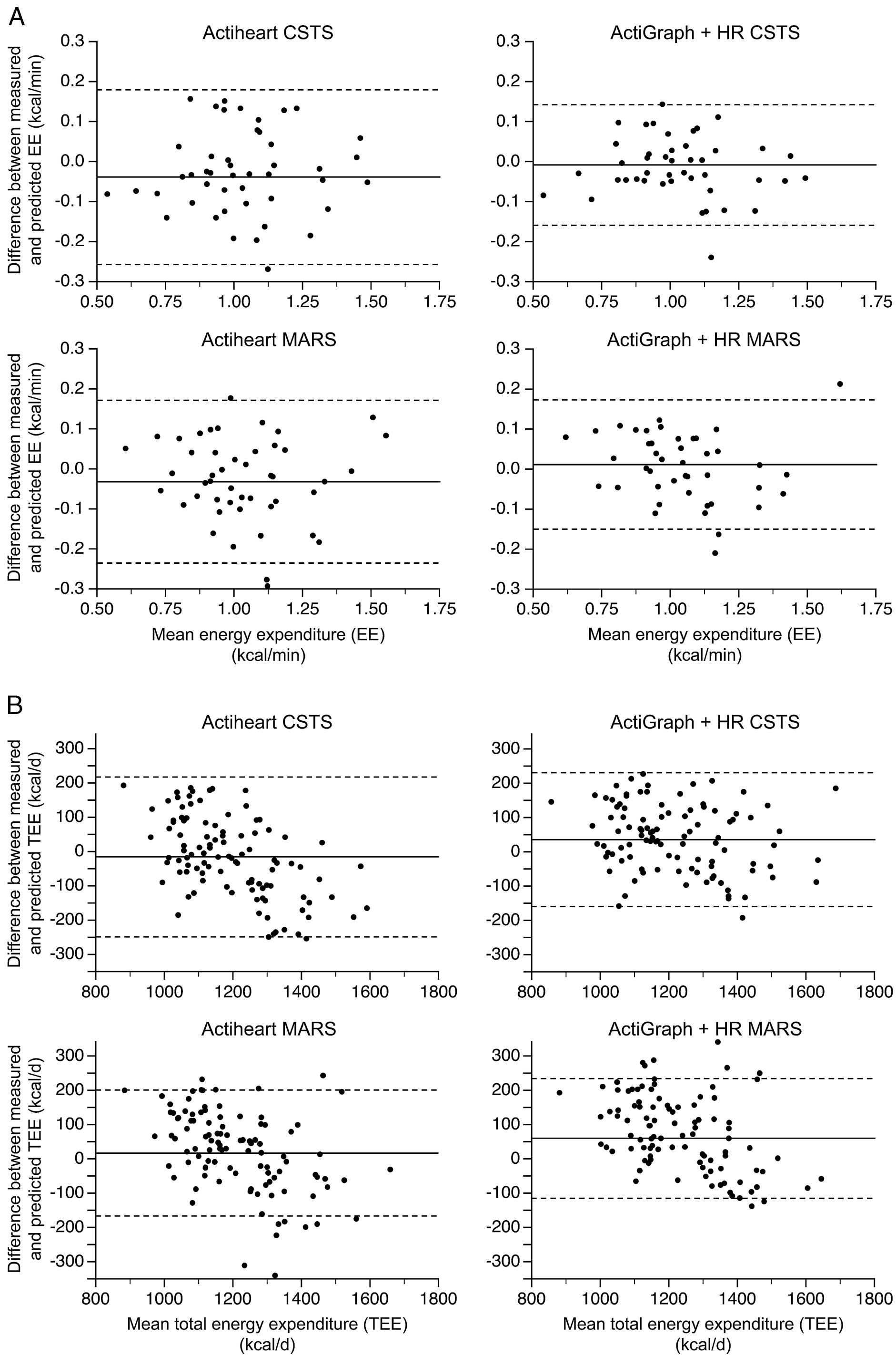

FIGURE 1—A, Bland–Altman plots evaluating the prediction of EE by CSTS and MARS models using Actiheart and ActiGraph devices versus energy expenditure measured by room respiration calorimetry (*n* = 50). The mean difference between measured EE and predicted EE is plotted against the mean of the two methods; the mean bias is shown by a *solid line* and the 95% limits of agreement are shown by *dash lines*. B, Bland–Altman plots evaluating the prediction of TEE by CSTS and MARS models using Actiheart and ActiGraph devices versus TEE measured by DLW method (*n* = 105). The mean difference between measured TEE and predicted TEE is plotted against the mean of the two methods; the mean bias is shown by a *solid line* and the 95% limits of agreement are shown by *dash lines*. CSTS = cross-sectional time series; DLW = doubly labeled water; EE = energy expenditure; MARS = multivariate adaptive regression splines.

were narrowest for the CSTS ActiGraph+HR compared to the other models. Predicted TEE values were within 1SD (184 kcal$\cdot$d^{-1}) of the DLW-TEE for 89% and 93% of the children based on the CSTS Actiheart and ActiGraph+HR models, respectively, and for 85% and 80% of the children based on the MARS Actiheart and ActiGraph+HR models, respectively. The CCC between the measured and predicted TEE values were 0.73 and 0.82 for the CSTS models and

TABLE 3. Prediction errors of the CSTS and MARS models for the prediction of TEE versus doubly labeled water method, presented as mean absolute error, percent error, and RMSE.

	CSTS Model		MARS Model	
	Actiheart	ActiGraph + HR	Actiheart	ActiGraph + HR
Mean absolute error (kcal·d^{-1})	−19 ± 115	41 ± 97	27 ± 123	79 ± 115
Mean percent error (%)	−0.5 ± 9.7	4.1 ± 8.5	3.2 ± 10.1	7.5 ± 10
RMSE (kcal·d^{-1})	116	105	125	139

[a] n = 105; data are given as means and standard deviation.
CSTS = cross-sectional time series; HR = heart rate; MARS = multivariate adaptive regression splines; RMSE = root mean square error; TEE = total energy expenditure.

0.73 and 0.69 for the MARS models using Actiheart and ActiGraph+HR, respectively.

Accelerometer count cut points for sedentary, light, moderate, and vigorous levels of physical activity in preschool-age children. Smoothing splines curve fitting was applied to established HR cut points (110, 140, and 160 bpm) to define AEE (0.013, 0.052, and 0.073 kcal·kg^{-1}·min^{-1}) levels corresponding to the boundaries for sedentary/light, light/moderate, and moderate/vigorous PA (Fig. 2). Applying the AEE thresholds, the following initial accelerometer cut points were determined using smoothing splines: 36, 449, and 1297 cpm for Actiheart *x*-axis; 610, 3908, and 6112 cpm for ActiGraph vector magnitude; and 110, 2120, and 4450 cpm for ActiGraph *x*-axis. Using the initial cut points, ROC curves were constructed and maximal sensitivity + specificity rates were computed, considering two activity levels at a time (1 vs 2, 2 vs 3, or 3 vs 4, defining 1 as sedentary, 2 as light, 3 as moderate, and 4 as vigorous). The number of points used for constructing ROC plots varied; there were 13,468 points for the 1 versus 2 comparison; 7126 points for the 2 versus 3 comparison; and 1629 points for the 3 versus 4 comparison. Because the number of points was smaller and the search range for the threshold was larger for the 3 versus 4 comparison than for the others, the ROC curves for the 3 versus 4 comparison were less concave. On the basis of the maximal sensitivity + specificity rates, the cut points determined by the ROC curves were 41, 261, and 1180 cpm for Actiheart; 820, 2830, and 6282 cpm for ActiGraph vector magnitude; and 240, 1170, and 3800 cpm for ActiGraph *x*-axis. Different combinations of cut points based on the

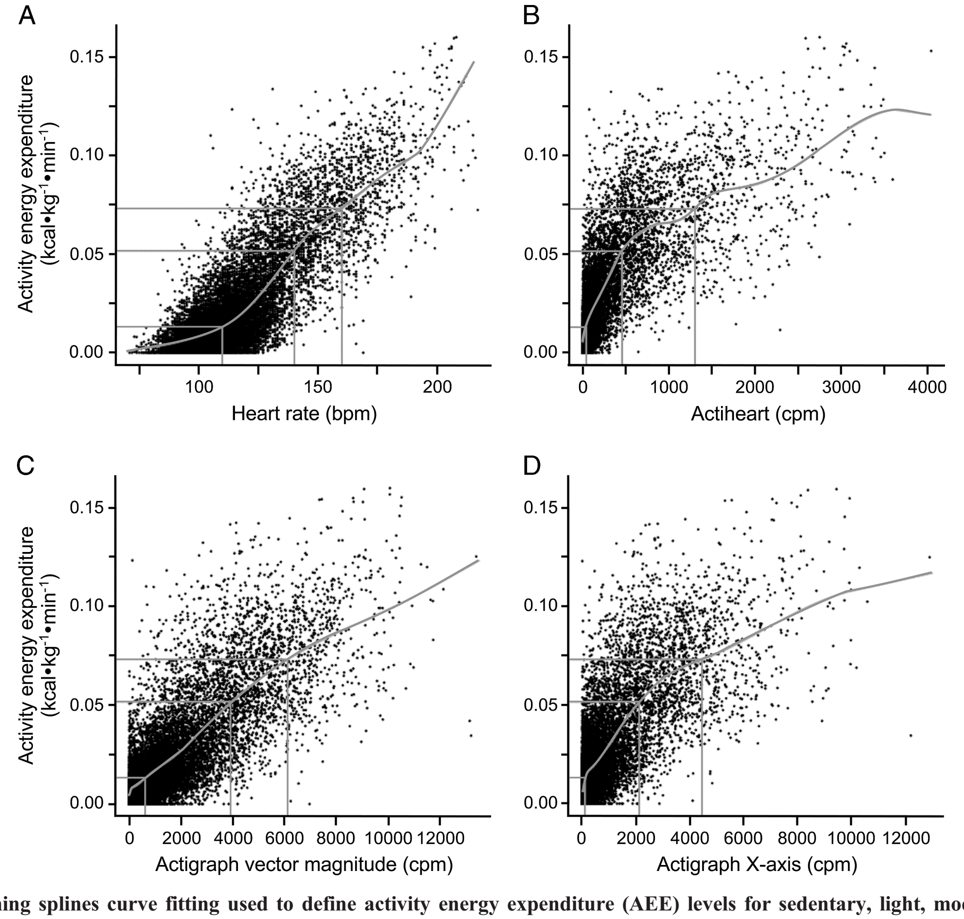

FIGURE 2—Smoothing splines curve fitting used to define activity energy expenditure (AEE) levels for sedentary, light, moderate, and vigorous physical activity in preschool-age children from heart rate thresholds (A); smoothing splines curve fitting applied to the AEE and accelerometer counts to identify accelerometer cut points for Actiheart *x*-axis (B), ActiGraph vector magnitude (C), and ActiGraph *x*-axis (D).

smoothing splines and ROC results were tried, and the majority vote was used to determine the best classifier (i.e., the cut point combination that provided the highest correct classification rate from the confusion matrix).

The final cut points for Actiheart *x*-axis, ActiGraph vector magnitude, and ActiGraph *x*-axis are presented in Table 4. On the basis of the confusion matrices, the correctly classified rates were 81%, 64%, 48%, and 39% for Actiheart; 83%, 64%, 35%, and 38% for ActiGraph vector magnitude; and 82%, 58%, 37%, and 29% for ActiGraph *x*-axis for sedentary, light, moderate, and vigorous levels of PA, respectively. Using the diagonals of confusion matrices, the overall accuracy rates were 70% for Actiheart, 70% for ActiGraph vector magnitude, and 68% for ActiGraph *x*-axis. If moderate and vigorous PA (MVPA) levels are collapsed, the correctly classified rates would be 81%, 64%, and 73% for Actiheart; 83%, 64%, and 63% for ActiGraph vector magnitude; and 82%, 58%, and 62% for ActiGraph *x*-axis for sedentary PA, light PA, and MVPA, respectively. Using the diagonals of confusion matrices, the overall accuracy rates were 74% for Actiheart, 74% for ActiGraph vector magnitude, and 71% for ActiGraph *x*-axis.

DISCUSSION

CSTS and MARS population-specific models for the prediction of minute-by-minute EE from accelerometry and HR monitoring in preschool-age children were validated using room respiration calorimetry in a controlled laboratory setting and DLW under free-living conditions. Room calorimetry allowed us to evaluate minute-by-minute EE data, whereas DLW allowed us to evaluate the performance of the models over a 7-d period. Importantly, these are population-specific models for preschool-age children that do not require individual calibration in the laboratory. The models include child characteristics that provide some individual specification (age, sex, weight, height, and sleeping HR) but do not require measurement of the HR–EE or AC–EE relationships in individual children.

In both the development and validation protocols, the samples of children were racially/ethnically diverse and balanced for age and sex. The prevalence of overweight/obesity was less in our development (20%) and validation (12%) cohorts than the national average (27%). However, our prediction errors were not significantly associated with age, sex, weight, height, or BMI *z*-scores; therefore, we are confident that our models are robust for preschool children who have characteristics in the range of our sample.

TABLE 4. Accelerometer count cutoffs for sedentary/light, light/moderate, and moderate/vigorous cutoffs for physical activity in preschool-age children.

	Sedentary/ Light	Light/ Moderate	Moderate/ Vigorous
Actiheart *x*-axis (cpm)	41	449	1297
ActiGraph vector magnitude (cpm)	820	3908	6112
ActiGraph *x*-axis (cpm)	240	2120	4450

cpm = counts per minute.

Calorimeter validation of the CSTS and MARS models. For the calorimeter validation, a wide range of EE and HR values was attained inside the calorimeter room with minimum values observed during sleep and near-maximum values during running in place. Relative to calorimetry, mean percent errors for the CSTS and MARS models for all EE data were acceptable, ranging from ±7.4% to ±10.8%. The Bland–Altman plots indicated a lack of bias and acceptable limits of agreement. The high concordance between the predicted and measured EE (CCC = 0.86–0.93) affirms the validity of the models for preschool-age children.

The ActiGraph CSTS and MARS models implemented during awake time outperformed the ActiGraph+HR models. For investigators who elect to use ActiGraph GT3X+ during awake time only, EE can be predicted accurately with accelerometry using the ActiGraph CSTS or MARS models. If an estimate of the 24-h TEE is desired, the Schofield equation for BMR can be used to estimate sleep EE. We found that the Schofield prediction of basal EE agreed with measured sleep EE within −2.8% ± 10.1%.

DLW validation of the CSTS and MARS models. Relative to the DLW method, mean percent errors ranging from 8.5% to 10.1% were comparable to the errors attained for the CSTS and MARS models in the calorimetry validation. There was a lack of bias with the Actiheart CSTS model and a slightly positive bias with the other models and acceptable 95% limits of agreement. The concordance between the predicted and measured EE (CCC = 0.69–0.82) affirms the validity of the models for preschool-age children. The DLW is an excellent method for measuring average TEE under free-living conditions, but its application does involve several assumptions and potential sources of error (25). Validations against respiratory calorimetry have demonstrated that the method is accurate and has a precision of 2%–8%, depending on the loading dose, the length of the metabolic period, and the number of samples (26). Given the fact that both calorimetry and the DLW method have their own inherent errors, we consider the limits of agreement with the CSTS and MARS models acceptable. Although subject characteristics (age, sex, and weight) account for a large proportion of the variance in TEE, the level of PA varies considerably between children. In this study, the PA level (PAL = TEE/BMR) ranged from 1.05 to 1.69; however, this variable component of TEE was captured objectively by accelerometry and HR monitoring.

CSTS and MARS models for the prediction of EE in preschoolers were developed and validated here across a wide range of body sizes, levels of EE, and PA and should therefore be robust for similar populations of preschool-age children. Although the CSTS and MARS models performed comparably, there are inherent differences in the two approaches. CSTS is a parametric approach to model a collection of correlated data, taking into account within-individual changes and between-individual heterogeneity (6,13). CSTS models explicitly distinguish between-subject and within-subject sources of variability and allow for subject-specific description of the mean response profile. MARS is a multivariate nonparametric regression that approximates a complex relationship (nonlinear) by a series of spline functions on different intervals of the independent variable (10). The CSTS models seem to be more robust to outliers than the MARS models. For 24-h applications, the Actiheart or ActiGraph+HR models are recommended. For awake periods only, the Actiheart, ActiGraph+HR, or ActiGraph models can be used. Although model development required sophisticated statistical software, the CSTS and MARS models can be easily implemented using standard statistical programs or computational spreadsheets such as Excel.

Accelerometer count cut points for sedentary, light, moderate, and vigorous levels of PA in preschool-age children. Actiheart and ActiGraph cut points for PA levels have been estimated based on direct observations (5,24,28) and respiration calorimetry (2,21). Direct observation methods are reliant on human observation, interpretation, and recording of activity and are thus inherently subjective. The intensity of PA is difficult to quantify by observation alone. Because considerable variability is seen in the AC and EE for any given activity in preschoolers, it was critical to base PA categorization on a quantitative rather than a qualitative criterion. We chose to use AEE (0.013, 0.052, and 0.073 $kcal \cdot kg^{-1} \cdot min^{-1}$) based on established HR thresholds of 110 bpm for sedentary/light, 140 bpm for light/moderate, and 160 bpm for moderate/vigorous levels of PA (7). These thresholds equate to 1.5, 2.8, and 3.5 child-specific metabolic equivalents (METs), comparable to those derived in Adolph et al. (2). Our accelerometer cut points for moderate and vigorous PA corresponding to 2.8 and 3.5 child METs are generally lower than the criteria used in older children and adolescents (32), reflecting the lower levels of AEE achievable and sustainable in developmentally immature preschoolers (2,21,22,29,30). The relatively higher BMR in preschoolers compared to older children also confound the interpretation of MET values in these young children. Given the developmental differences and distinct relationships between HR, AC, and EE in preschoolers compared with older children, age-specific EE prediction equations and accelerometer cut points are necessary.

The overall classification accuracy of the cut points (68%–70%) was similar among Actiheart, ActiGraph vector magnitude, and ActiGraph *x*-axis. The specific classified rates were acceptable for sedentary and light but not for moderate and vigorous levels of PA. In concordance with our previous publication (2), there was substantial overlap of AC between the moderate and vigorous PA levels as seen by the large dispersion around the AEE–AC relationship. Clear partitioning of AC between moderate and vigorous PA may be a limitation of accelerometer use in preschoolers because they do not attain or sustain high levels of physical exertion for extended periods. However, if moderate and vigorous levels of PA are collapsed, the correctly classified rates for the MVPA category improve substantially to 73%, 63%, and 62% and the overall classification accuracy of the cut points improved to 74%, 74%, and 71% for Actiheart, ActiGraph vector magnitude, and ActiGraph *x*-axis, respectively. In practicality, preschoolers spend only a small percent of awake time in vigorous PA; therefore, the collapsed category of MVPA may be more meaningful for health outcomes.

We can compare our final cut points for sedentary, light, moderate, and vigorous PA levels with published values for Actiheart and ActiGraph *x*-axis. Because GT3X+ vector magnitude is a new feature, cut points have not been published previously. For the ActiGraph *x*-axis, our sedentary cut point was similar to that of Trost et al. (31), but was much lower than those of Reilly et al. (24), Sirard et al. (28), and van Cauwenberghe et al. (36), probably because of different statistical approaches, because the definition of sedentary activities was similar across studies, i.e., stationary/no movement or stationary/no trunk movement. Our moderate and vigorous cut points were slightly higher than those of Pate et al. (21) and Trost et al. (31), but lower than those of Sirard et al. (28). Pate et al. predicted moderate and vigorous PA thresholds by a linear equation relating AC and $\dot{V}O_2$. Applying this equation to our calorimeter data, we found that $\dot{V}O_2$ was overestimated by 10%–20% depending on the activity. In their calibration study, overestimation of $\dot{V}O_2$ would have resulted in lower ActiGraph cut points for moderate and vigorous PA. For Actiheart, our cut points are higher than those published earlier (2) because of the structure of the data and curve fitting procedures used. Our Actiheart cut points are lower than those recommended by de Bock et al. (5) for sedentary/light but similar for light/moderate boundaries.

Although there is much precedent in the literature for simple accelerometer cut points for PA levels, this approach inevitably results in some misclassification of AC between PA categories. Furthermore, simple cut points do not take advantage of the richness of the accelerometer data that include acceleration in three directions, steps, and position. A multidimensional approach that incorporates all the AC data and considers the surrounding AC counts (i.e., lag and lead values) may be superior for the classification of PA levels. The research field is moving toward classification methods such as machine learning, pattern recognition, and neural net; in fact, we have published one article on machine learning using this data set (42). These more advanced classification methods, too, require boundaries based on external criteria for their development.

In conclusion, CSTS and MARS models based on child characteristics, accelerometry, and HR monitoring were validated for the prediction of minute-by-minute EE in preschool-age children. Relative to the room respiration calorimetry and the DLW method, the mean bias and limits of agreement indicate that the CSTS and MARS models are acceptable for the prediction of EE in preschool-age children. Accelerometer cut points were satisfactory for the classification of sedentary PA, light PA, and MVPA in preschoolers. Therefore, CSTS and MARS models using nonintrusive, inexpensive devices can be used to measure EE and PA levels of preschool-age children in their natural settings.

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